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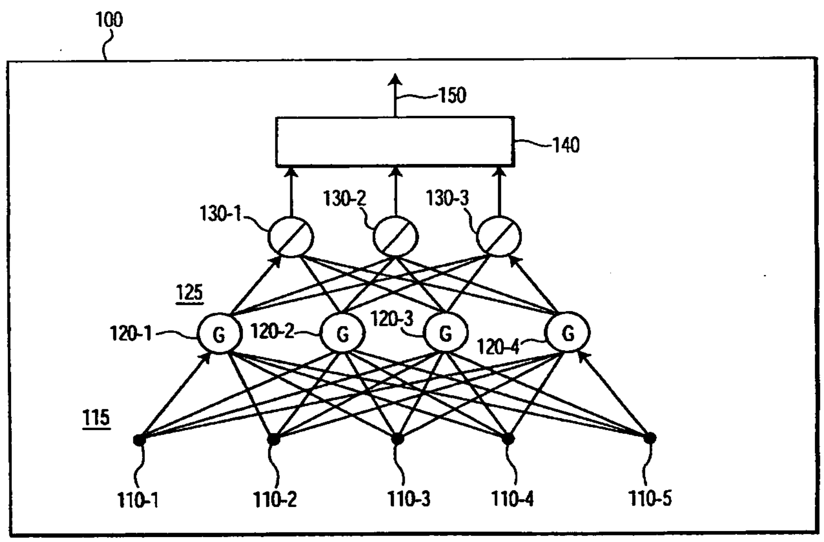
(54) Title: COMPUTER VISION SYSTEM AND METHOD EMPLOYING ILLUMINATION INVARIANT NEURAL NETWORKS



(57) Abstract: Objects are classified using a normalized cross correlation (NCC) measure to compare two images acquired under non-uniform illumination conditions. An input pattern is classified to assign a tentative classification label and value. The input pattern is assigned to an output node in the radial basis function network having the largest classification value. If the input pattern and an image associated with the node, referred to as a node image, both have uniform illumination, then the node image is accepted and the probability is set above a user specified threshold. If the test image or the node image are not uniform, then the node image is not accepted and the classification value is kept as the value assigned by the classifier. If both the test image and the node image are not uniform, then an NCC measure is used and the classification value is set as the NCC value.

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COMPUTER VISION SYSTEM AND METHOD EMPLOYING ~~ILLUMINATION INVARIANT NEURAL NETWORKS~~

The present invention relates to computer vision systems, and more particularly, to the classification of objects in image data using Radial Basis Function Networks (RBFNs).

Computer vision techniques are frequently used to automatically detect or classify objects or events in images. The ability to differentiate among objects is an important task for the efficient functioning of many computer vision systems. For example, in certain applications it is important for a computer vision system to distinguish between animate objects, such as people and pets, and inanimate objects, such as furniture and doors. Pattern recognition techniques, for example, are often applied to images to determine a likelihood (probability) that a given object or class of objects appears in the image. For a detailed discussion of pattern recognition or classification techniques, see, for example, R. O. Duda and P. Hart, Pattern Recognition and Scene Analysis, Wiley, New York (1973); R.T. Chin and C.R. Dyer, "Model-Based Recognition in Robot Vision," ACM Computing Surveys, 18(1), 67–108 (March, 1986); or P.J. Besl and R.C. Jain, "Three-Dimensional Object Recognition," Computing Surveys, 17(1), 75–145 (March, 1985), each incorporated by reference herein.

Appearance based techniques have been extensively used for object recognition because of their inherent ability to exploit image based information. Appearance based techniques attempt to recognize objects by finding the best match between a two-dimensional image representation of the object appearance and stored prototypes. Generally, appearance based methods use a lower dimensional subspace of the higher dimensional representation for the purpose of comparison. United States Patent Application Serial Number 09/794,443, filed February 27, 2001, entitled "Classification of Objects Through Model Ensembles," for example, discloses an object classification engine that distinguishes between people and pets in a residential home environment. Initially, speed and aspect ratio information are used to filter out invalid moving objects, such as furniture. Thereafter, gradient images are extracted from the remaining objects and applied to a radial basis function network to classify moving objects as people or pets.

Generally, a radial basis function network involves three different layers. An input layer is made up of source nodes, often referred to as input nodes. The second

layer is a hidden layer, comprised of hidden nodes, whose function is to cluster the data and, generally, to reduce its dimensionality to a limited degree. The output layer supplies the response of the network to the activation patterns applied to the input layer. The transformation from the input space to the hidden-unit space is non-linear, whereas the transformation from the hidden-unit space to the output space is linear. A radial basis function network is initially trained using example images of objects to be recognized. When presented with image data to be recognized, the radial basis function network computes the distance between the input data and each hidden node. The computed distance provides a score that can be used to classify an object.

If the training images and the test images to be classified are not acquired under similar illumination conditions, the comparison of the input image with each hidden node will be erroneous, thereby leading to poor classification or recognition. A need therefore exists for an improved method and apparatus for comparing images acquired under non-uniform illumination conditions.

Generally, a method and apparatus are disclosed for classifying objects under varying illumination conditions. The disclosed classifier uses an improved neural network, such as a radial basis function network, to classify objects. The classifier employs a normalized cross correlation (NCC) measure to compare two images acquired under non-uniform illumination conditions.

An input pattern to be classified is initially processed using conventional classification techniques to assign a tentative classification label and classification value (sometimes referred to as a "probability value") to the input pattern. Generally, an input pattern is assigned to an output node in the radial basis function network having the largest classification value. Thereafter, according to one aspect of the invention, it is determined whether the input pattern and the image associated with the node to which the input pattern was classified, referred to as a node image, have uniform illumination.

If the test image and the node image are both uniform, then the node image is accepted and the probability is set to a value above a user specified threshold. If the test image is uniform and the node image is not uniform (or vice versa), then the image is not accepted and the classification value is kept as the same value as assigned by the classifier. Finally, if both the test image and the node image are not uniform, then a normalized cross correlation measure is used and the classification value is set as the NCC value.

A more complete understanding of the present invention, as well as further features and advantages of the present invention, will be obtained by reference to the following detailed description and drawings.

FIG. 1 illustrates an exemplary prior art classifier that uses Radial Basis Functions (RBFs);

FIG. 2 is a schematic block diagram of an illustrative pattern classification system in accordance with the present invention;

FIG. 3 is a flow chart describing an exemplary RBFN training process for training the pattern classification system of FIG. 2; and

FIG. 4 is a flow chart describing an exemplary object classification process for using the pattern classification system of FIG. 2 for pattern recognition and classification.

The present invention provides an object classification scheme that employs an improved radial basis function network for comparing images acquired under non-uniform illumination conditions. While the exemplary embodiment discussed herein employs Radial Basis Function Networks, it is noted that other neural networks could be similarly employed, such as back propagation networks, multi-layered perceptron-based networks and Bayesian-based neural networks, as would be apparent to a person of ordinary skill in the art. For example, neural networks based on Principle Component Analysis (PCA) or Independent Component Analysis (ICA), or a classifier based on Bayesian techniques or Linear Discriminant Analysis (LDA), could also be employed, as would be apparent to a person of ordinary skill.

FIG. 1 illustrates an exemplary prior art classifier 100 that uses Radial Basis Functions (RBFs). As previously indicated, construction of an RBF neural network used for classification involves three different layers. An input layer is made up of source nodes, referred to herein as input nodes. The second layer is a hidden layer whose function is to cluster the data and, generally, to reduce its dimensionality to a limited degree. The output layer supplies the response of the network to the activation patterns applied to the input layer. The transformation from the input space to the hidden-unit space is non-linear, whereas the transformation from the hidden-unit space to the output space is linear.

Thus, the classifier 100 comprises (1) an input layer comprising input nodes 110 and unit weights 115, which connect the input nodes 110 to hidden nodes 120; (2) a

"hidden layer" comprising hidden nodes 120; and (3) an output layer comprising linear weights 125 and output nodes 130. For pattern recognition and classification, a select maximum device 140 and a final output 150 are added.

It is noted that unit weights 115 are such that each connection from an input node 110 to a hidden node 120 essentially remains the same (i.e., each connection is "multiplied" by a one). However, linear weights 125 are such that each connection between a hidden node 120 and an output node 130 is multiplied by a weight. The weight is determined and adjusted during a training phase, as described below in conjunction with FIG. 3.

In the example of FIG. 1, there are five input nodes 110, four hidden nodes 120, and three output nodes 130. However, FIG. 1 is merely exemplary and, in the description given below, there are D input nodes 110, F hidden nodes 120, and M output nodes 130. Each hidden node 120 has a Gaussian pulse nonlinearity specified by a particular mean vector μ_i and variance vector σ_i^2, where $i = 1, \ldots, F$ and F is the number of hidden nodes 120. Note that σ_i^2 represents the diagonal entries of the covariance matrix of Gaussian pulse i. Given a D-dimensional input vector X, each BF node i outputs a scalar value y_i, reflecting the activation of the BF caused by that input, as follows:

$$y_i = \varphi_i(\|X - \mu_i\|) = \exp\left[-\sum_{k=1}^{D} \frac{(x_k - \mu_{ik})^2}{2h\sigma_{ik}^2}\right], \qquad \{1\}$$

where h is a proportionality constant for the variance, x_k is the kth component of the input vector $X = [x_1, x_2, \ldots, x_D]$, and μ_{ik} and φ_{ik} are the kth components of the mean and variance vectors, respectively, of basis node i. Inputs that are close to the center of a Gaussian BF result in higher activations, while those that are far away result in lower activations. Since each output node of the RBF classifier 100 forms a linear combination of the hidden node 120 activations, the part of the network 100 connecting the middle and output layers is linear, as shown by the following:

$$z_j = \sum_i w_{ij} y_i + w_{oj}, \qquad \{2\}$$

where z_j is the output of the jth output node, y_i is the activation of the ith BF node, w_{ij} is the weight connecting the ith BF node to the jth output node, and w_{oj} is the bias or threshold of the jth output node. This bias comes from the weights associated with a hidden node 120 that has a constant unit output regardless of the input.

An unknown vector X is classified as belonging to the class associated with the output node j with the largest output z_j, as selected by the select maximum device 140. The select maximum device 140 compares each of the outputs from the M output nodes to determine final output 150. The final output 150 is an indication of the class that has been selected as the class to which the input vector X corresponds. The linear weights 125, which help to associate a class for the input vector X, are learned during training. The weights w_{ij} in the linear portion of the classifier 100 are generally not solved using iterative minimization methods such as gradient descent. Instead, they are usually determined quickly and exactly using a matrix pseudoinverse technique. This technique and additional information about RBF classifiers are described, for example, in R. P. Lippmann and K. A. Ng, "Comparative Study of the Practical Characteristic of Neural Networks and Pattern Classifiers," MIT Technical Report 894, Lincoln Labs. (1991); C. M. Bishop, "Neural Networks for Pattern Recognition," Ch. 5 (1995); J. Moody & C.J. Darken, "Fast Learning in Networks of Locally Tuned Processing Units", Neural Computation, vol. 1, 281-94 (1989); or Simon Haykin, "Neural Networks: A Comprehensive Foundation," Prentice Hall, 256-317 (1999), each incorporated by reference herein.

A detailed algorithmic description of an exemplary radial basis function classifier is discussed below in conjunction with FIGS. 3 and 4. Initially, the size of the RBF network is determined by selecting F, the number of hidden nodes. The appropriate value of F is problem-specific and usually depends on the dimensionality of the problem and the complexity of the decision regions to be formed. In general, F can be determined empirically by trying a variety of Fs, or it can set to some constant number, usually larger than the input dimension of the problem.

After F is set, the mean m_i and variance σ_i^2 vectors of the BFs can be determined using a variety of methods. They can be trained, along with the output weights,

using a back-propagation gradient descent technique, but this usually requires a long training time and may lead to suboptimal local minima. Alternatively, the means and variances can be determined before training the output weights. Training of the networks would then involve only determining the weights.

The BF centers and variances are normally chosen so as to cover the space of interest. Different techniques have been suggested. One such technique uses a grid of equally spaced BFs that sample the input space. Another technique uses a clustering algorithm such as K-means to determine the set of BF centers, and others have chosen random vectors from the training set as BF centers, making sure that each class is represented. For a further discussion of RBFNs, see, for example, United States Patent Application Serial Number 09/794,443, filed February 27, 2001, entitled "Classification of Objects Through Model Ensembles," incorporated by reference herein.

Generally, each Radial Basis Function classifier 100 will indicate the probability that a given object is a member of the class associated with the corresponding node. For a discussion of the extraction of horizontal, vertical and combined gradients from the input intensity images for use as the feature vectors, see, for example, United States Patent Application Serial Number 09/794,443, filed February 27, 2001, entitled "Classification of Objects Through Model Ensembles," incorporated by reference herein. Generally, the process involves processing a collection of sequences of a set of model objects, and extracting horizontal, vertical and combined gradients for each object to form a set of image vectors corresponding to each object.

FIG. 2 is an illustrative pattern classification system 200 using the radial basis function network 100 of FIG. 1, as modified in accordance with the invention. FIG. 2 comprises a pattern classification system 200, shown interacting with input patterns 210 and Digital Versatile Disk (DVD) 250, and producing classifications 240.

Pattern classification system 200 comprises a processor 220 and a memory 230, which itself comprises an RBFN training process 300, discussed below in conjunction with FIG. 3, and an object classification process 400, discussed below in conjunction with FIG. 4. Pattern classification system 200 accepts input patterns and classifies the patterns. For example, the input patterns could be images from a video, and the pattern classification system 200 can be used to distinguish humans from pets.

The pattern classification system 200 may be embodied as any computing device, such as a personal computer or workstation, containing a processor 220, such as a central processing unit (CPU), and memory 230, such as Random Access Memory (RAM) and Read-Only Memory (ROM). In an alternate embodiment, the pattern classification system 200 disclosed herein can be implemented as an application specific integrated circuit (ASIC), for example, as part of a video processing system.

As is known in the art, the methods and apparatus discussed herein may be distributed as an article of manufacture that itself comprises a computer readable medium having computer readable code means embodied thereon. The computer readable program code means is operable, in conjunction with a computer system, to carry out all or some of the steps to perform the methods or create the apparatuses discussed herein. The computer readable medium may be a recordable medium (e.g., floppy disks, hard drives, compact disks such as DVD 250, or memory cards) or may be a transmission medium (e.g., a network comprising fiber-optics, the world-wide web, cables, or a wireless channel using time-division multiple access, code-division multiple access, or other radio-frequency channel). Any medium known or developed that can store information suitable for use with a computer system may be used. The computer readable code means is any mechanism for allowing a computer to read instructions and data, such as magnetic variations on a magnetic media or height variations on the surface of a compact disk, such as DVD 250.

Memory 230 will configure the processor 220 to implement the methods, steps, and functions disclosed herein. The memory 230 could be distributed or local and the processor 220 could be distributed or singular. The memory 230 could be implemented as an electrical, magnetic or optical memory, or any combination of these or other types of storage devices. The term "memory" should be construed broadly enough to encompass any information able to be read from or written to an address in the addressable space accessed by processor 220. With this definition, information on a network is still within memory 250 of the pattern classification system 300 because the processor 220 can retrieve the information from the network.

FIG. 3 is a flow chart describing an exemplary implementation of the RBFN training process 400 of FIG. 2. As is known in the art, training a pattern classification system is generally performed in order for the classifier to be able to categorize patterns

into classes. Generally, the RBFN training process 300 is employed to train the Radial Basis Function neural network 100, using image data from an appropriate ground truth data set that contains an indication of the correct object classification. As previously indicated, each of the connections in the Radial Basis Function neural network 100 between the input layer 110 and the pattern (hidden layer) 120 and between the pattern (hidden layer) 120 and the output layer 130 are assigned weights during the training phase.

As shown in FIG. 3, the exemplary RBFN training process 300 initializes the RBF network 100 during step 310. As previously indicated, the initialization process typically involves the following steps:

(a) fixing the network structure by selecting F, the number of basis functions, where each basis function I has the following output:

$$y_i = \phi_i(\|X - \mu_i\|) = \exp\left[-\sum_{k=1}^{D} \frac{(x_k - \mu_{ik})^2}{2h\sigma^2_{ik}}\right],$$

where k is the component index;

(b) determining the basis function means μ_I, where I equals 1, ... , F, using a K-means clustering algorithm;

(c) determining the basis function variances σ_I^2, where I equals 1, ... , F (the basis function variances σ_I^2 can be fixed to some global value or set to reflect the density of the data vectors in the vicinity of the BF center); and

(d) determining H, a global proportionality factor for the basis function variances by empirical search to allow for rescaling of the BF widths (by searching the space of *H* for values that result in good performance, its proper value is determined).

After the BF parameters are set, the next step is to train the output weights. Thus, the exemplary RBFN training process 300 presents the training image data to the initialized RBF network 100 during step 320. In one embodiment, the training image presentation process typically involves the following steps:

(a) inputting training patterns *X(p)* and their class labels *C(p)* to the classifier, where the pattern index is *p* equals *1, ... , N*;

(b) computing the output of the basis function nodes $y_I(p)$, where *I* equals *1, ... , F*, resulting from pattern *X(p)*;

(c) computing the $F \times F$ correlation matrix **R** of the basis function outputs, as follows:

$$R_{il} = \sum_p y_i(p) y_l(p)$$

(d) computing the $F \times M$ output matrix **B**, where d_j is the desired output and M is the number of output classes, as follows:

$$B_{lj} = \sum_p y_l(p) d_j(p),\ where\ d_j(p) = \begin{cases} 1\ if\ C(p) = j \\ 0\ \ otherwise \end{cases},$$

and $j = 1, \ldots, M$.

It is noted that each training pattern produces one **R** and one **B** matrix. The final **R** and **B** matrices are the result of the sum of N individual **R** and **B** matrices, where N is the total number of training patterns. Once all N patterns have been presented to the classifier, the output weights w_{ij} can be determined.

Thus, the exemplary RBFN training process 300 determines the output weights w_{ij} for the RBF network 100 during step 330. In one embodiment, the weights for the initialized RBF network 100 are calculated as follows:

(a) inverting the final $F \times F$ correlation matrix **R** to get $\mathbf{R}^{-1}$; and

(b) solving for the weights in the network using the following equation:

$$w^*_{ij} = \sum_l \left(R^{-1}\right)_{il} B_{lj}$$

Thereafter, program control of the RBFN training process 300 terminates.

For a further discussion of training techniques for Radial Basis Function classifiers 100, see, for example, United States Patent Application Serial Number 09/794,443, filed February 27, 2001, entitled "Classification of Objects Through Model Ensembles," incorporated by reference herein.

FIG. 4 is a flow chart describing an exemplary object classification process 400 incorporating features of the present invention. As shown in FIG. 4, the exemplary object classification process 400 begins in step 410, when an unknown pattern, X_{test}, is presented or obtained. It is noted that the image, X_{test}, can be preprocessed to filter out unintended moving objects from detected moving objects, for example, according to a detected speed and aspect ratio of each detected moving object, in a known manner.

During step 420, the input pattern, X_{test}, is applied to the Radial Basis Function classifier 100 to compute the classification value. Thereafter, the input pattern, X_{test}, is classified by the RBF network 100 during step 430 using conventional techniques. In one implementation the input pattern, X_{test}, is classified as follows:

(a) computing the basis function outputs, for all F basis functions, as follows:

$$y_i = \phi(\|X_{test} - \mu_i\|)$$

(b) computing output node activations, as follows:

$$z_j = \sum_i w_{ij} y_i + w_{oj}$$

(c) selecting the output z_j with the largest value and classify $\mathbf{X}_{test}$ as the class j.

The RBF input generally consists of n size normalized face images fed to the network 100 as 1D vectors. The hidden (unsupervised) layer, implements an enhanced k-means clustering procedure, where both the number of Gaussian cluster nodes and their variances are dynamically set. The number of clusters varies, in steps of 5, from 1/5 of the number of training images to n, the total number of training images. The width of the Gaussian for each cluster, is set to the maximum (the distance between the center of the cluster and the farthest away member; within class diameter, the distance between the center of the cluster and closest pattern from all other clusters) multiplied by an overlap factor o, here equal to 2. The width is further dynamically refined using different proportionality constants h. The hidden layer yields the equivalent of a functional face base, where each cluster node encodes some common characteristics across the face space. The output (supervised) layer maps face encodings ("expansions") along such a space to their corresponding ID classes and finds the corresponding expansion ("weight") coefficients using pseudoinverse techniques. It is noted that the number of clusters is frozen for that configuration (the number of clusters and specific proportionality constant h) which yields 100 % accuracy on ID classification when tested on the same training images.

According to one feature of the present invention, test is performed during step 440 to determine if the classification value assigned to the input pattern during step 430 is below a predefined, configurable threshold. If it is determined during step 430 that

the classification value is not below the threshold, then program control terminates. If, however, it is determined during step 430 that the classification value is below the threshold, then further processing is performed during steps 450 through 480 to determine if the poor classification value is due to non-uniform illumination.

Thus, the input pattern, X_{test}, and the image associated with the hidden node to which X_{Test} was classified are evaluated during step 450 to determine if they have uniform illumination. For example, to ascertain if an image is uniform, the intensity values are normalized to lie between 0 and 1. Thereafter, the image is divided into a number of regions and the mean and the variance are computed. If the mean and variance are within a range between any two regions, then the image is said to be uniform.

If it is determined during step 450 that the test image and the hidden node to which the classifier assigned the test image are both uniform, then the image is accepted during step 460 and the probability is set to a value above the user specified threshold.

If it is determined during step 450 that the test image is uniform and the hidden node is not uniform (or vice versa), then the image is not accepted during step 470 and the classification value is kept as the same value as assigned by the classifier 100.

Finally, if it is determined during step 450 that both the test image and the hidden node are not uniform, then the normalized cross correlation (NCC) measure is used during step 480 and the classification value is set as the NCC value. The equation for NCC is expressed as follows:

$$NCC = \frac{\sum (x_i - \bar{x}) \cdot (r_i - \bar{r})}{\sqrt{\sum (x_i - \bar{x})^2 \cdot \sum (r_i - \bar{r})^2}}$$

where x is the test image and r is the hidden node. NCC is usually performed by dividing the test and the hidden node into a number of sub regions and then summing the computation on each one of the regions. Generally, the NCC will smooth the images by matching segments within each image and determining how far each segment is from a mean. Thereafter, the deviation from mean values for each segment are averaged.

In a further variation, the network 100 is trained in accordance with FIG. 3. Thereafter, for each test image, a Eucliedian distance metric is computed. For whichever node the distance is minimum, the image associated with the minimum node and the test image are processed using only steps 450 through 480 of FIG. 4.

It is to be understood that the embodiments and variations shown and described herein are merely illustrative of the principles of this invention and that various modifications may be implemented by those skilled in the art without departing from the scope and spirit of the invention.

CLAIMS:

1. A method for classifying an object in image data, comprising the steps of: assigning said image data to a node in a neural network, said node having an associated node image; and
applying a normalized cross correlation measure to compare said image data and said node image if said image data and said node image are obtained under non-uniform illumination.

2. The method of claim 1, wherein a classification value for said object is determined by said normalized cross correlation measure.

3. The method of claim 1, wherein a determination of whether an image is obtained under non-uniform illumination further comprises the steps of normalizing intensity values in said image, dividing said image into a number of regions, computing the mean and the variance of said regions and determining if said image is uniform based on said mean and variance values.

4. The method of claim 1, wherein said classification value associated with said node is assigned to said image data if both of said image data and said node image are obtained under uniform illumination.

5. The method of claim 1, wherein said node image is not accepted if only one of said image data and said node image are obtained under uniform illumination.

6. The method of claim 1, wherein said applying step is only performed if said classification value does not satisfy a predefined threshold.

7. The method of claim 1, wherein said node has an associated class label identifying a class to which the object corresponds to and a classification value indicating the probability with which the object belongs to the class.

8. The method of claim 1, further comprising the step of outputting a class label based upon said normalized cross correlation measure.

9. The method of claim 1, wherein said neural network is a radial basis function network.

10. The method of claim 1, wherein said neural network is a back propagation network.

11. The method of claim 1, wherein said neural network is a multi-layered perceptron-based network.

12. The method of claim 1, wherein said neural network is a Bayesian-based neural network.

13. An apparatus for classifying an object in image data, comprising:
a memory; and
at least one processor, coupled to the memory, operative to:
assign said image data to a node in a neural network, said node having an associated node image; and
apply a normalized cross correlation measure to compare said image data and said node image if said image data and said node image are obtained under non-uniform illumination.

14. The apparatus of claim 13, wherein a classification value for said object is determined by said normalized cross correlation measure.

15. The apparatus of claim 13, wherein said processor is further configured to determine whether an image is obtained under non-uniform illumination by normalizing intensity values in said image, dividing said image into a number of regions, computing the mean and the variance of said regions and determining if said image is uniform based on said mean and variance values.

16. The apparatus of claim 13, wherein said classification value associated with said node is assigned to said image data if both of said image data and said node image are obtained under uniform illumination.

17. The apparatus of claim 13, wherein said node image is not accepted if only one of said image data and said node image are obtained under uniform illumination.

18. The apparatus of claim 13, wherein said node has an associated class label identifying a class to which the object corresponds to and a classification value indicating the probability with which the object belongs to the class.

19. The apparatus of claim 13, wherein said neural network is a radial basis function network.

20. The apparatus of claim 13, wherein said neural network is a back propagation network.

21. The apparatus of claim 13, wherein said neural network is a multi-layered perceptron-based network.

22. The apparatus of claim 13, wherein said neural network is a Bayesian-based neural network.

23. An article of manufacture for classifying an object in image data, comprising:
a machine readable medium containing one or more programs which when executed implement the steps of:
assigning said image data to a node in a neural network, said node having an associated node image; and
applying a normalized cross correlation measure to compare said image data and said node image if said image data and said node image are obtained under non-uniform illumination.

PATENT COOPERATION TREATY

From the INTERNATIONAL SEARCHING AUTHORITY

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NOTIFICATION OF TRANSMITTAL OF THE INTERNATIONAL SEARCH REPORT OR THE DECLARATION

(PCT Rule 44.1)

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1. [x] The applicant is hereby notified that the International Search Report has been established and is transmitted herewith.

Filing of amendments and statement under Article 19:
The applicant is entitled, if he so wishes, to amend the claims of the International Application (see Rule 46):

When? The time limit for filing such amendments is normally 2 months from the date of transmittal of the International Search Report; however, for more details, see the notes on the accompanying sheet.

Where? Directly to the International Bureau of WIPO
34, chemin des Colombettes
1211 Geneva 20, Switzerland
Fascimile No.: (41-22) 740.14.35

For more detailed instructions, see the notes on the accompanying sheet.

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2. [ ] The applicant is hereby notified that no International Search Report will be established and that the declaration under Article 17(2)(a) to that effect is transmitted herewith.

3. [ ] **With regard to the protest** against payment of (an) additional fee(s) under Rule 40.2, the applicant is notified that:

[ ] the protest together with the decision thereon has been transmitted to the International Bureau together with the applicant's request to forward the texts of both the protest and the decision thereon to the designated Offices.

[ ] no decision has been made yet on the protest; the applicant will be notified as soon as a decision is made.

4. **Further action(s):** The applicant is reminded of the following:

Shortly after **18 months** from the priority date, the international application will be published by the International Bureau. If the applicant wishes to avoid or postpone publication, a notice of withdrawal of the international application, or of the priority claim, must reach the International Bureau as provided in Rules 90*bis*.1 and 90*bis*.3, respectively, before the completion of the technical preparations for international publication.

Within **19 months** from the priority date, a demand for international preliminary examination must be filed if the applicant wishes to postpone the entry into the national phase until 30 months from the priority date (in some Offices even later).

Within **20 months** from the priority date, the applicant must perform the prescribed acts for entry into the national phase before all designated Offices which have not been elected in the demand or in a later election within 19 months from the priority date or could not be elected because they are not bound by Chapter II.

Name and mailing address of the International Searching Authority	Authorized officer
European Patent Office, P.B. 5818 Patentlaan 2 NL-2280 HV Rijswijk Tel. (+31-70) 340-2040, Tx. 31 651 epo nl, Fax: (+31-70) 340-3016	Franco Spanu

NOTES TO FORM PCT/ISA/220

These Notes are intended to give the basic instructions concerning the filing of amendments under article 19. The Notes are based on the requirements of the Patent Cooperation Treaty, the Regulations and the Administrative Instructions under that Treaty. In case of discrepancy between these Notes and those requirements, the latter are applicable. For more detailed information, see also the PCT Applicant's Guide, a publication of WIPO.

In these Notes, "Article", "Rule", and "Section" refer to the provisions of the PCT, the PCT Regulations and the PCT Administrative Instructions respectively.

INSTRUCTIONS CONCERNING AMENDMENTS UNDER ARTICLE 19

The applicant has, after having received the international search report, one opportunity to amend the claims of the international application. It should however be emphasized that, since all parts of the international application (claims, description and drawings) may be amended during the international preliminary examination procedure, there is usually no need to file amendments of the claims under Article 19 except where, e.g. the applicant wants the latter to be published for the purposes of provisional protection or has another reason for amending the claims before international pbulication. Furthermore, it should be emphasized that provisional protection is available in some States only.

What parts of the international application may be amended?

Under Article 19, only the claims may be amended.

During the international phase, the claims may also be amended (or further amended) under Article 34 before the International Preliminary Examining Authority. The description and drawings may only be amended under Article 34 before the International Examining Authority.

Upon entry into the national phase, all parts of the international application may be amended under Article 28 or, where applicable, Article 41.

When? Within 2 months from the date of transmittal of the international search report or 16 months from the priority date, whichever time limit expires later. It should be noted, however, that the amendments will be considered as having been received on time if they are received by the International Bureau after the expiration of the applicable time limit but before the completion of the technical preparations for international publication (Rule 46.1).

Where not to file the amendments?

The amendments may only be filed with the International Bureau and not with the receiving Office or the International Searching Authority (Rule 46.2).

Where a demand for international preliminary examination has been/is filed, see below.

How? Either by cancelling one or more entire claims, by adding one or more new claims or by amending the text of one or more of the claims as filed.

A replacement sheet must be submitted for each sheet of the claims which, on account of an amendment or amendments, differs from the sheet originally filed.

All the claims appearing on a replacement sheet must be numbered in Arabic numerals. Where a claim is cancelled, no renumbering of the other claims is required. In all cases where claims are renumbered, they must be renumbered consecutively (Administrative Instructions, Section 205(b)).

The amendments must be made in the language in which the international application is to be published.

What documents must/may accompany the amendments?

Letter (Section 205(b)):

The amendments must be submitted with a letter.

The letter will not be published with the international application and the amended claims. It should not be confused with the "Statement under Article 19(1)" (see below, under "Statement under Article 19(1)").

The letter must be in English or French, at the choice of the applicant. However, if the language of the international application is English, the letter must be in English; if the language of the international application is French, the letter must be in French.

The letter must indicate the differences between the claims as filed and the claims as amended. It must, in particular, indicate, in connection with each claim appearing in the international application (it being understood that identical indications concerning several claims may be grouped),whether

(i) the claim is unchanged;

(ii) the claim is cancelled;

(iii) the claim is new;

(iv) the claim replaces one or more claims as filed;

(v) the claim is the result of the division of a claim as filed.

The following examples illustrate the manner in which amendments must be explained in the accompanying letter:

1. [Where originally there were 48 claims and after amendment of some claims there are 51]: "Claims 1 to 29, 31, 32, 34, 35, 37 to 48 replaced by amended claims bearing the same numbers; claims 30, 33 and 36 unchanged; new claims 49 to 51 added."

2. [Where originally there were 15 claims and after amendment of all claims there are 11]: "Claims 1 to 15 replaced by amended claims 1 to 11."

3. [Where originally there were 14 claims and the amendments consist in cancelling some claims and in adding new claims]: "Claims 1 to 6 and 14 unchanged; claims 7 to 13 cancelled; new claims 15, 16 and 17 added." or "Claims 7 to 13 cancelled; new claims 15, 16 and 17 added; all other claims unchanged."

4. [Where various kinds of amendments are made]: "Claims 1-10 unchanged; claims 11 to 13, 18 and 19 cancelled; claims 14, 15 and 16 replaced by amended claim 14; claim 17 subdivided into amended claims 15, 16 and 17; new claims 20 and 21 added."

"Statement under article 19(1)" (Rule 46.4)

The amendments may be accompanied by a statement explaining the amendments and indicating any impact that such amendments might have on the description and the drawings (which cannot be amended under Article 19(1)).

The statement will be published with the international application and the amended claims.

It must be in the language in which the international appplication is to be published.

It must be brief, not exceeding 500 words if in English or if translated into English.

It should not be confused with and does not replace the letter indicating the differences between the claims as filed and as amended. It must be filed on a separate sheet and must be identified as such by a heading, preferably by using the words "Statement under Article 19(1)."

It may not contain any disparaging comments on the international search report or the relevance of citations contained in that report. Reference to citations, relevant to a given claim, contained in the international search report may be made only in connection with an amendment of that claim.

Consequence if a demand for international preliminary examination has already been filed

If, at the time of filing any amendments under Article 19, a demand for international preliminary examination has already been submitted, the applicant must preferably, at the same time of filing the amendments with the International Bureau, also file a copy of such amendments with the International Preliminary Examining Authority (see Rule 62.2(a), first sentence).

Consequence with regard to translation of the international application for entry into the national phase

The applicant's attention is drawn to the fact that, where upon entry into the national phase, a translation of the claims as amended under Article 19 may have to be furnished to the designated/elected Offices, instead of, or in addition to, the translation of the claims as filed.

For further details on the requirements of each designated/elected Office, see Volume II of the PCT Applicant's Guide.

PATENT COOPERATION TREATY

PCT

INTERNATIONAL SEARCH REPORT

(PCT Article 18 and Rules 43 and 44)

Applicant's or agent's file reference PHUS020522WO	**FOR FURTHER ACTION** see Notification of Transmittal of International Search Report (Form PCT/ISA/220) as well as, where applicable, item 5 below.	
International application No. PCT/IB 03/05747	International filing date *(day/month/year)* 08/12/2003	(Earliest) Priority Date *(day/month/year)* 11/12/2002
Applicant KONINKLIJKE PHILIPS ELECTRONICS N.V.		

This International Search Report has been prepared by this International Searching Authority and is transmitted to the applicant according to Article 18. A copy is being transmitted to the International Bureau.

This International Search Report consists of a total of 4 sheets.

[X] It is also accompanied by a copy of each prior art document cited in this report.

1. **Basis of the report**
   a. With regard to the **language**, the international search was carried out on the basis of the international application in the language in which it was filed, unless otherwise indicated under this item.
      [ ] the international search was carried out on the basis of a translation of the international application furnished to this Authority (Rule 23.1(b)).
   b. With regard to any **nucleotide and/or amino acid sequence** disclosed in the international application, the international search was carried out on the basis of the sequence listing :
      [ ] contained in the international application in written form.
      [ ] filed together with the international application in computer readable form.
      [ ] furnished subsequently to this Authority in written form.
      [ ] furnished subsequently to this Authority in computer readble form.
      [ ] the statement that the subsequently furnished written sequence listing does not go beyond the disclosure in the international application as filed has been furnished.
      [ ] the statement that the information recorded in computer readable form is identical to the written sequence listing has been furnished

2. [ ] **Certain claims were found unsearchable** (See Box I).
3. [ ] **Unity of invention is lacking** (see Box II).

4. With regard to the **title,**
   [X] the text is approved as submitted by the applicant.
   [ ] the text has been established by this Authority to read as follows:

5. With regard to the **abstract,**
   [X] the text is approved as submitted by the applicant.
   [ ] the text has been established, according to Rule 38.2(b), by this Authority as it appears in Box III. The applicant may, within one month from the date of mailing of this international search report, submit comments to this Authority.

6. The figure of the **drawings** to be published with the abstract is Figure No. 1
   [X] as suggested by the applicant.
   [ ] because the applicant failed to suggest a figure.
   [ ] because this figure better characterizes the invention.
   [ ] None of the figures.

INTERNATIONAL SEARCH REPORT

International Application No
T/IB 03/05747

A. CLASSIFICATION OF SUBJECT MATTER
IPC 7 G06K9/00

According to International Patent Classification (IPC) or to both national classification and IPC

B. FIELDS SEARCHED

Minimum documentation searched (classification system followed by classification symbols)
IPC 7 G06K

Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched

Electronic data base consulted during the international search (name of data base and, where practical, search terms used)

EPO-Internal, WPI Data, INSPEC, PAJ

C. DOCUMENTS CONSIDERED TO BE RELEVANT

Category °	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
X	BRUNELLI R ET AL: "FACE RECOGNITION: FEATURES VERSUS TEMPLATES" IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, IEEE INC. NEW YORK, US, vol. 15, no. 10, 1 October 1993 (1993-10-01), pages 1042-1052, XP000403523 ISSN: 0162-8828 abstract; page 1043-1044, section II.A. "Normalization"; page 1046, last paragraph, continued on page 1047, Fig.10; page1047, last paragraph; page1048, last paragraph, continued on page 1049, Fig.19 ----- -/--	1-5, 13-17,23

[X] Further documents are listed in the continuation of box C.

[X] Patent family members are listed in annex.

° Special categories of cited documents :

"A" document defining the general state of the art which is not considered to be of particular relevance

"E" earlier document but published on or after the international filing date

"L" document which may throw doubts on priority claim(s) or which is cited to establish the publication date of another citation or other special reason (as specified)

"O" document referring to an oral disclosure, use, exhibition or other means

"P" document published prior to the international filing date but later than the priority date claimed

"T" later document published after the international filing date or priority date and not in conflict with the application but cited to understand the principle or theory underlying the invention

"X" document of particular relevance; the claimed invention cannot be considered novel or cannot be considered to involve an inventive step when the document is taken alone

"Y" document of particular relevance; the claimed invention cannot be considered to involve an inventive step when the document is combined with one or more other such documents, such combination being obvious to a person skilled in the art.

"&" document member of the same patent family

Date of the actual completion of the international search	Date of mailing of the international search report
25 May 2004	17/06/2004

Name and mailing address of the ISA	Authorized officer
European Patent Office, P.B. 5818 Patentlaan 2 NL – 2280 HV Rijswijk Tel. (+31-70) 340-2040, Tx. 31 651 epo nl, Fax: (+31-70) 340-3016	Grigorescu, C

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INTERNATIONAL SEARCH REPORT

International Application No
T/IB 03/05747

C.(Continuation) DOCUMENTS CONSIDERED TO BE RELEVANT

Category °	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
A	US 5 842 194 A (ARBUCKLE THOMAS D) 24 November 1998 (1998-11-24) the whole document -----	1-23
A	US 5 239 594 A (YODA FUMIO) 24 August 1993 (1993-08-24) the whole document -----	1-23
A	EGMONT-PETERSEN M ET AL: "Image processing with neural networks-a review" PATTERN RECOGNITION, PERGAMON PRESS INC. ELMSFORD, N.Y, US, vol. 35, no. 10, October 2002 (2002-10), pages 2279-2301, XP004366785 ISSN: 0031-3203 the whole document -----	1-23

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INTERNATIONAL SEARCH REPORT

Information on patent family members

International Application No
PCT/IB 03/05747

Patent document cited in search report	Publication date	Patent family member(s)	Publication date
US 5842194 A	24-11-1998	NONE	
US 5239594 A	24-08-1993	JP 4288663 A	13-10-1992

Form PCT/ISA/210 (patent family annex) (January 2004)